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TEXTURE FUNCTIONS IN IMAGE ANALYSIS: A COMPUTATIONALLY EFFICIENT SOLUTION

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TEXTURE FUNCTIONS IN IMAGE ANALYSIS:
A COMPUTATIONALLY EFFICIENT SOLUTION

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TEXTURE FUNCTIONS IN IMAGE ANALYSIS:

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ABSTRACT

A set of statistics that measures visually perceivable textures in images by use of co-occurrence matrices has previously been developed. Presented here is a computationally efficient means for calculating texture measurements from digital images by use of the co-occurrence technique. This paper discusses the calculation of the statistical descriptors of image texture and presents a solution that circumvents the need for calculating and storing a co-occurrence matrix. The results show that existing efficient algorithms for calculating sums, sums of squares, and cross products can be used to compute complex co-occurrence relationships directly from the digital image input.

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CONTENTS

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TEXTURE FUNCTIONS IN IMAGE ANALYSIS:

A COMPUTATIONALLY EFFICIENT SOLUTION

1.0 INTRODUCTION

This paper presents a computationally efficient solution developed as part of the Multispectral Linear Array Supporting Science Studies (MLASSS) at the Goddard Space Flight Center (GSFC), for calculating texture statistics from digital images. Presented here are the mathematical foundations of image-texture calculations based on the Spatial Grey Tone Dependence (SGTD) method developed by Haralick (1) and Haralick et al. (2) and reviewed by Conners (3) and Conners and Harlow (4).

One aim of the MLASSS is to determine the synergistic effects of increased sensor spatial, spectral, and radiometric resolution. Spatial resolution studies at GSFC have focused in increases in image information content with increased spatial resolution and evaluation of sensor systems with mixed spatial resolution as possible candidates for future land remote-sensing missions. To this end texture analysis, in particular SGTD, was seen as one way to quantify the increased spatial information apparent in high-resolution digital imagery. This paper documents the development and use of software at GSFC to implement Haralick's algorithms.

2.0 BACKGROUND

Landsat-4's successful launch and subsequent successful operation of the Thematic Mapper (TM) and Multispectral Scanner (MSS) heralded a new era in space-based remote sensing. Advances include improved spatial resolution of 30-meters instantaneous field-of-view, 7 spectral bands and 8-bit quantization for the TM. In the future, multispectral linear array (MLA) technology will

make it possible to obtain digital imagery of vastly improved spatial resolution, 10 to 15-m in the visible and near infrared (5). In anticipation of this increased capability, several investigators have used high-resolution aircraft scanner data to study the tradeoffs associated with increased spatial resolution, processing strategies, and costs. A potentially serious problem has been encountered in the use of conventional unsupervised or supervised per-pixel classifiers: as spatial resolution increases, classification accuracies tend to diminish in areas of high spatial complexity (6). Furthermore, as the proportion of mixed pixels increases, classification accuracies decrease. An example would be the decreasing classification accuracy of small agricultural fields whose size approaches the sensor IFOV. Conversely, heterogeneous land covers characterized by small high-frequency components tend to be averaged at lower resolutions so that classification accuracies are higher with per-pixel classifiers. These results have been independently confirmed by Latty (7) for forested sites.

These studies point to a need to incorporate spatial information in the classification process. Several methods have been advocated in addition to Haralick's SGTD method; they include spatial/spectral context, used by Tilton and Swain (8), and categorical/spatial context, developed by Wharton (9). This paper discusses the Haralick SGTD algorithm and derives a computationally efficient means for calculating various texture statistics derived from a spatial gray-tone co-occurrence matrix.

Texture analysis as discussed in this paper is used to quantify the spatial information in a digital image by measuring the spatial arrangement of gray tones within it. The recent literature includes a review of various texture-analysis methods by Haralick (2) and an update by Davis (10).

Conners and Harlow (4) investigated the theoretical merits of various texture-analysis strategies for quantifying image patterning. Cox et al. (11) and Weszka et al. (12) conducted empirical comparisons of various texture measures.

The SGTD method has been used frequently by investigators working with remotely sensed data, including Haralick et al. (1), Hsu (13), Jensen (14) and Toll (15), Schowengerdt (16), and Weszka et al. (12). Compared to first-order statistics such as mean and standard deviation, SGTD has greater potential but is computationally more complex. The SGTD method transforms the gray values within a neighborhood (window) into a two-dimensional gray-tone co-occurrence of gray-tone pairs i and j as measured among angle a for distance d and can be interpreted as a probability matrix of gray-tone pairs. Haralick et al. (1) introduced a number of statistics based on information theory to describe such matrices, and as part of the spatial studies of the MLASSS, eight have been put to use at GSFC on the HP-3000-based Interactive Digital Image Manipulation System (IDIMS) in the Applications Directorate. What follows is a discussion of these eight algorithms and their implementation.

3.0 CO-OCCURRENCE CALCULATIONS

Given a rectangular matrix (window) of values (brightness), an occurrence matrix is defined as the frequency with which a value of i precedes a value of j in the direction α. Call this matrix $q_{ij}(\alpha)$.

A co-occurrence matrix is defined as

$$P_{ij}(\alpha) = q_{ij}(\alpha) + q_{ij}(\alpha+\pi)$$

or the sum of the occurrence matrix in one direction plus the occurrence matrix in the opposite direction.

It should be noted that

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$$q_{ij}(\alpha+\pi) = q_{ji}(\alpha)$$

and

$$q_{ij}(\alpha) = q_{ji}(\alpha+\pi)$$

That is, the number of times i precedes j in direction α is exactly the number of times j precedes i in the opposite $(\alpha+\pi)$ direction.

Consequently

$$P_{ij}(\alpha) = q_{ij}(\alpha) + q_{ji}(\alpha)$$

or alternatively

$$P_{ij}(\alpha) = q_{ij}(\alpha) + q'_{ij}(\alpha)$$

Where $q'_{ij}(\alpha)$ is the transpose of $q_{ij}(\alpha)$.

Further relationships between the co-occurrence matrix and the occurrence, or precedence, matrix can be readily seen.

The sum of all elements within the matrix

$$\sum_{i}^{NI}\sum_{j}^{NJ} P_{ij}(\alpha) = \sum_{i}^{NI}\sum_{j}^{NJ} q_{ij}(\alpha) + \sum_{i}^{NI}\sum_{j}^{NJ} q'_{ij}(\alpha)$$

$$= 2\sum_{i}^{NI}\sum_{j}^{NJ} q_{ij}(\alpha); \text{ due to symmetry}$$

Furthermore, since the precedence matrix (q) is strictly a count of relationships within the window of precedence, the sum of that matrix is simply the number of relationships within that window. Since each cell specifies a single relationship within the precedence matrix

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$$\sum_{i}^{NI}\sum_{j}^{NJ} P_{ij}(\alpha) = 2N_\alpha; \text{ where } N_\alpha \text{ is the number of } \alpha\text{-pairs}$$

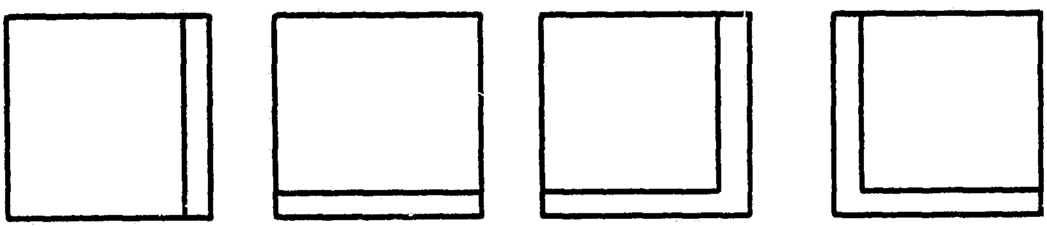
In a similar fashion

$$\Sigma\Sigma_i{}^2 P_{ij} = \Sigma\Sigma_i{}^2 q_{ij} + \Sigma\Sigma_j{}^2 q'_{ij}$$

and

$$\Sigma\Sigma_{ij} P_{ij} = \Sigma\Sigma_{ij} q_{ij} + \Sigma\Sigma_{ji} q'_{ij}$$
$$= 2\,\Sigma\Sigma_{ij} q_{ij}; \text{ due to symmetry.}$$

The occurrence matrix q is more literally a precedence matrix in that it is a count of the number of times a value i precedes a value j in direction α. The particular values that precede occur in a subset of the original window, depending on the direction α. Specifically, in the diagrams below the range of precedence is indicated.



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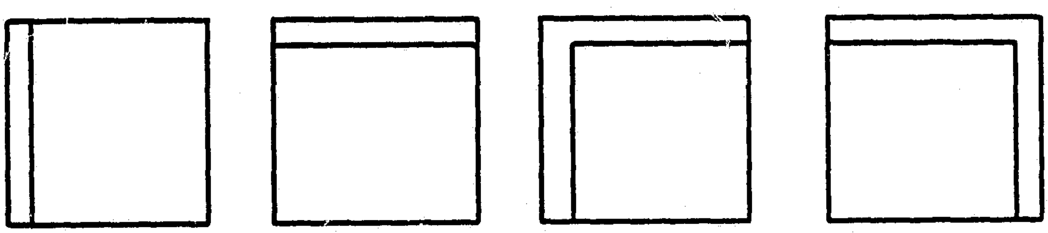
Range of Precedence

Similarly, the range of succession depends on the direction α.



0° 90° 45° 135°

Range of Succession

It should be noted in these diagrams that the number of rows (scan lines) and the number of columns (pixels) within the range of precedence both depend on the direction α. However, for any given direction α the limits on the range of precedence are equivalent to the limits on the range of succession.

The average brightness value within the range of precedence can be expressed in two ways. The brightness value times the relative frequency of occurrence of that brightness—summed—is one way to express the mean:

$$\mu = \sum_{i=1}^{NV} if_i$$

Expressed in the language of precedence and co-occurrence, that relative frequency is the relative number of times which that brightness (i) preceded all other brightness values.

$$fi = \frac{\sum_{j=1}^{NV} qij}{N_\alpha}$$ where N_α is the total number of α=pairs

Thus, one expression for the mean is

$$\mu = \frac{1}{N} \Sigma i \Sigma q_{ij} = \frac{1}{N_\alpha} \Sigma\Sigma i q_{ij}$$

A more efficient method of calculating the average brightness within the range of precedence is only to sum all brightness values and divide by the number of α-pairs.

$$\mu = \sum_{k}^{NS} \sum_{l}^{NR} x_{kl}/N_\alpha$$

Where NS and NR are the limits of the range of precedence.

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The equivalence of these two measures of average brightness points out that

$$\sum_{i}^{NV}\sum_{j}^{NV} iq_{ij} = \sum_{k}^{NS}\sum_{l}^{NR} X_{kl}$$

In a similar fashion it can be demonstrated that for the range of succession

$$\sum_{i}^{NV}\sum_{j}^{NV} jq'_{ij} = \sum_{k}^{MS}\sum_{l}^{MR} X_{kl}$$

Where MS and MR are the limits of the range of succession.

Again, for higher order moments of precedence or succession it can be shown that

$$\Sigma\Sigma i^2 q_{ij} = \Sigma\Sigma X^2_{kl}$$

and

$$\Sigma\Sigma ijq_{ij} = \Sigma\Sigma_{kl} X_{k+a,l+b}$$

where a and b depend on the direction α.

Sum, sums of squares, and crossproducts are computationally efficient algorithms. These translations have made it possible to compute fairly complex co-occurrence relationships by use of computationally efficient techniques.

4.0 CALCULATION OF TEXTURE STATISTICS

Eight texture functions based on the pairs of co-occurrence were developed. The background and application of these functions has been fully described elsewhere (1, 2, 3, 4).

Of the eight functions, three (variance, skewness, kurtosis) can be phrased readily in a computationally efficient form. Three further functions (difference moment, homogeneity, correlation), which are based on the co-occurrence matrix approach, can be reduced to a more efficient

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and standard form. The last two functions (energy, entropy) have not yielded an efficient solution and still require co-occurrence calculations.

4.1 Variance, Skewness, Kurtosis

Within each window the first four moments of the brightness values were calculated. Define

$$\mu_r' = \frac{1}{n}\Sigma X^r$$

Then

$$\mu_1 = \mu_1'$$

$$\mu_2 = \mu_2' - (\mu_1')^2$$

$$\mu_3 = \mu_3' - 3\mu_2'\mu_1' + 2(\mu_1')^3$$

$$\mu_4 = \mu_4' - 4\mu_3\mu_1 + 6\mu_2(\mu_1')^2 - 3(\mu_1')^4 \quad .$$

Using those definitions, the variance is

$$\sigma^2 = \frac{N\mu_2}{(N-1)}$$

The coefficient of skewness is defined as

$$\sqrt{b_1} = \frac{\mu_3}{(\mu_2)^{3/2}}$$

And the coefficient of kurtosis is given as

$$b_2 = \frac{\mu_4}{\mu_2^2}$$

These statistics require only that the four raw moments (μ_r') be accumulated for each pixel within a window as a whole.

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4.2 Difference Moment

The co-occurrence formulation of the difference moment function is

$$\psi = \sum_{i}^{NV} \sum_{j}^{NV} (i-j)^2 P_{ij}$$

Since this is a symmetric function $[(i-j)^2 = (j-i)^2]$ occurrence, or precedence, matrix formulation is

$$\psi = 2 \sum_{i}^{NV} \sum_{j}^{NV} (i-j)^2 q_{ij}$$

This is again the standard grouped-data formulation of a moment. Writing it in more efficient ungrouped format,

$$\psi = \frac{2}{N_\alpha} \Sigma\Sigma (X_1 - X_2)^2$$

Where the X_1 values are the brightness values of preceding pixels and the X_2 values are the values of their successors. The summation is over the full range of precedence.

4.3 Homogeneity

The co-occurrence formulation of homogeneity is

$$\Gamma = \sum_{i}^{NV} \sum_{j}^{NV} \frac{1}{1 + (i-j)^2} P_{ij}$$

Once again we can observe the symmetry, and the precedence formulation is similar:

$$\Gamma = 2 \sum_{i}^{NV} \sum_{j}^{NV} \frac{1}{1 + (i-j)^2} q_{ij}$$

And finally, the more standard ungrouped form of this moment equation:

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$$\Gamma = \frac{2}{N} \Sigma\Sigma \frac{1}{1 + (X_1 - X_2)^2}$$

4.4 Correlation

The co-occurrence formulation of this function has been expressed as

$$\rho = \frac{\sum_i \sum_j (i-m)(j-m) P_{ij}}{\sum_i \sum_j (i-m)^2 P_{ij}}$$

where $m = \Sigma\Sigma i p_{ij} / \Sigma\Sigma p_{ij}$

In expanded form

$$\rho = \frac{\Sigma\Sigma ij p_{ij} - m\Sigma\Sigma i p_{ij} - m\Sigma\Sigma j p_{ij} + m^2 \Sigma\Sigma p_{ij}}{\Sigma\Sigma i^2 p_{ij} - 2m\Sigma\Sigma i p_{ij} + m^2 \Sigma\Sigma p_{ij}}$$

$\Sigma\Sigma j p_{ij} = \Sigma\Sigma i p_{ij}$ since P_{ij} is symmetric

and $\Sigma\Sigma i p_{ij} = m\Sigma\Sigma p_{ij}$

therefore

$$\rho = \frac{\Sigma\Sigma ij p_{ij} - m^2 \Sigma\Sigma p_{ij}}{\Sigma\Sigma i^2 p_{ij} - m^2 \Sigma\Sigma p_{ij}}$$

In terms of the precedence matrices the correlation can be expressed

$$\rho = \frac{2\Sigma\Sigma ij p_{ij} - 2m^2 N_\alpha}{\Sigma\Sigma i^2 q_{ij} + \Sigma\Sigma j^2 q_{ij}' - 2m^2 N_\alpha}$$

And in ungrouped terms

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$$\rho = \frac{\dfrac{\Sigma\Sigma X_1 X_2}{N_\alpha} - m^2}{\dfrac{1}{2}\left(\dfrac{\Sigma\Sigma X_1^2}{N_\alpha} + \dfrac{\Sigma\Sigma X_2^2}{N_\alpha}\right) - m^2}$$

In addition

$$m^2 = \left(\frac{\Sigma\Sigma i p_{ij}}{2N_\alpha}\right)^2$$

$$= \left(\frac{\Sigma\Sigma i q_{ij} + \Sigma\Sigma j q_{ij}'}{2N_\alpha}\right)^2$$

$$= \left(\frac{\Sigma\Sigma X_1}{2N_\alpha} \; \frac{\Sigma\Sigma X_2}{2N_\alpha}\right)^2$$

which is the square of the average of the mean precedence and the mean successor value.

4.5 Energy and Entropy

Neither of these functions has been found amenable to any simplification. The energy function has been expressed

$$E_1 = \sum_i^{NV} \sum_j^{NV} p_{ij}^2$$

and the entropy function

$$E_2 = \sum_i^{NV} \sum_j^{NV} [-p_{ij} \log p_{ij}]$$

As can be seen, both functions use nonlinear forms of the frequencies (not of the brightness values). This nonlinearity requires that the entire co-occurrence matrix be accumulated before the function can be evaluated. Since there is little limitation on the size of NV (spectral variance), these functions are notably expensive in terms of computer resources.

5.0 SUMMARY

We have presented a straightforward method of computing texture statistics from digital images. Based on the SGTD method, the computation of co-occurrence matrices is viewed as matrices of precedence and succession from which spatial/spectral relationships between neighboring pixels can be calculated. The precedence/succession method allows for the direct calculation of several texture statistics directly from the input data window without the need to calculate a time co-occurrence matrix as an intermediate step. This allows the realization of certain economies in memory and processing speed through the elimination of the co-occurrence matrix in the computation. However, instances in which individual co-occurrence matrix elements must be operated upon, the precedence/succession technique is not applicable.

REFERENCES

1. Haralick, R. M., Shanmaugam, K. and Dinstein, I., 1973. Textural Features for Image Classification, IEEE Transactions on Systems, Man and Cybernetics, SMC-3: 610-621.

2. Haralick, R. M., 1979. Statistical and Structural Approaches to Texture, Proceedings of the IEEE, 67: 786-804.

3. Conners, R. W., 1979. Towards A Set of Statistical Features Which Measure Visually Perceivable Qualities of Textures, Proceedings of the IEEE Computer Society Conference on Pattern Recognition and Image Processing, Chicago, Illinois, August 6-8.

4. Conners, R. W. and Harlow, C. A., 1980. A Theoretical Comparison of Texture Algorithms, IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMT-2: 204-222.

5. Mika, A. M., 1982. Design Tradeoffs for a Multispectral Linear Array (MLA) Instrument, in The Multispectral Imaging Science Working Group Final Report, Volume III—Contributed Papers, S. Cox, ed.; NASA Conference Publication, in press.

6. Markham, B. L. and Townshend, J. R. G., 1981. Land Cover Classification Accuracy as a Function of Sensor Spatial Resolution, Proceedings of the 15th International Symposium on Remote Sensing of Environment, Ann Arbor, Michigan (in press).

7. Latty, R. S., 1981. Computer Based Forest Cover Classification Using Multispectral Scanner Data of Different Spatial Resolutions, LARS Technical Report 052081, Laboratory for Applications of Remote Sensing, West Lafayette, Indiana, U.S.A.

8. Tilton, J. C. and Swain, P. H., 1981. Incorporating Spatial Context into Statistical Classification of Multidimensional Image Data, LARS Technical Report 072981, Laboratory for Applications of Remote Sensing, West Lafayette, Indiana, U.S.A.

9. Wharton, S. W., 1982. A Contextual Classification Method for Recognizing Land Use Patterns in High Resolution Remotely Sensed Data, Pattern Recognition, 15: 317-324.

10. Davis, L. S., 1982. Image Texture Analysis: Recent Development, in Proceedings of 1982 IEEE Conference on Pattern Recognition and Image Processing, Las Vegas, Nevada, pp. 214-127.

11. Cox, S. C., Bell, R., and Rose, J. F., 1981. A Quantitative Approach to Measurement of Information Content in Multiple Resolution Satellite Imagery, paper presented at the 10th Workshop on Applied Imagery Pattern Recognition, IEEE Computer Society, College Park, Maryland.

12. Weszka, J. S., Dyer, C. R., and Rosenfeld, A., 1979. A Comparative Study of Texture Measures for Terrain Classification, IEEE Transactions on Systems, Man and Cybernetics, SMC-6: 269-85.

13. Hsu, Shin-yi, Texture Tone Feature Extraction and Analysis. Rome Air Development Center Final Technical Report RADC-TR-77-279. August 1977. Air Force Systems Command, Griffiss Air Force Base, New York 13441.

14. Jensen, J. R., 1979. Spectral and Textural Functions to Classify Elusive Land Cover at the Urban Fringe, The Professional Geographer, 31: 400-409.

15. Jensen, J. R. and D. L. Toll, 1982. Detecting Residential Land-use Development at the Urban Fringe, Photogrammetric Engineering and Remote Sensing, 48: 629-643.

16. Schowengerdt, R. A., 1981. Texture Feature Extraction, final report, USGS Grant #14-08-001-g-664, Applied Remote Sensing Program, University of Arizona, Tucson, Arizona, U.S.A.